Bridging the technical and managerial side of big data analytics for supply chain planning: insight from a Delphi study

Jinou Xu (jinou.xu@polimi.it)
Department of Management, Economics and Industrial Engineering, Politecnico di Milano

Department of Management, Economics and Industrial Engineering, Politecnico di Milano

Federica Ciccullo
Department of Management, Economics and Industrial Engineering, Politecnico di Milano

Abstract

Big data analytics (BDA) has captured growing research interests in the supply chain domain, where supply chain management is often investigated as a broad topic. Limited research effort has addressed the link of BDA to the supply chain planning (SCP) processes. Through a Delphi study, this paper reveals insights from academicians and practitioners on *i)* matching BDA technology, big data sources and BDA impact to punctual SCP processes; and *ii)* managerial issues that affect the establishment of the link between BDA and SCP by investigating the determinants for BDA adoption decisions in supply chains.

Keywords: Big data, big data analytics, supply chain planning, Delphi research

1. Introduction

Big data analytics (BDA) has captured an increasing research effort in the supply chain domain. Empirical evidence on the use of BDA in supply chains is not scarce. Looking to the past, Amazon's anticipatory shipping managed to move goods close to customer location based on predictive analytics on customer purchasing behaviour and bundling habit (Mitchell, 2015). In a more recent term, big retailers are testing predictive and prescriptive BDA on Covid-19 breakout in forecasting the trend of the pandemic, and thus, making informed supply chain decisions on stock allocation and supplier backup (Burgess and Kidron, 2020). These are solely few examples that BDA is becoming one of the most prominent and disruptive technologies in supply chains to support strategic and operational decision-making (Accenture, 2014; O'Marah et al., 2014), for which both practitioners and academicians hold a faithful belief in its potential to elaborate data in attaining business insights.

While much research effort has been dedicated to investigate the overall contribution and challenges BDA might bring to the supply chain domain (show examples), only limited research has attempted to take a holistic view on the supply chain planning (SCP) process to address both the technical and managerial issues related to the link of BDA and SCP. Therefore, the research is set to address an overarching goal that is how can BDA be effectively linked to the SCP process? In response to such research objective, we further specified two research questions (RQ): *i) how can BDA technology be effectively matched with the need of individual SCP processes? ii) what factors should be prioritized in the managerial endeavours to support the BDA adoption decision in supply chains?*

The remainder of the paper is as follows. Section 2 introduces the research background, providing the backbone from literature, and section 3 explains the adopted methodology. The main findings of the study are presented in section 4, while section 5 continues with the discussion of these findings. The paper concludes with section 6 on the managerial implications and suggestions for future research.

2. Research background

2.1 Big data analytics

Big data refers to datasets that exceed the handling and storage capability of traditional data management systems (Russom, 2011; Wang et al., 2016), and are commonly defined by the dimensions of *volume*, *variety* and *velocity*, better known as the 3Vs (Russom, 2011). Big data can stem from diverse sources. *Structured* data typically refers standardized numbers and stings storedwith in the company databases, while *unstructured* data can range from texts, audio and video in social media, geospatial information, emails and internet log (Dubey et al., 2018). Borrowing the classification of supply chain risk sources, big data may also emerge from the inside of an *organization*, from the *network* of organizations or the external *environment* (Jüttner et al., 2003).

BDA stands for the application of advanced analytics on big data, aiming to extract meaningful patterns and insights to inform decision-making (Arunachalam et al., 2018; Wang et al., 2016). Extant studies identified various categories of analytics applicable in the big data context include classification, regression, clustering, association, visualization, semantic analysis, graphical analysis, optimization and simulation (Nguyen et al., 2018; Tiwari et al., 2018; Wang et al., 2016).

2.2 SCP processes

SCP stands for the activities associated with developing plans to operate supply chains, translating requirements to feasible programs and optimizing outcomes under certain constraints (Supply Chain Council, 2012). As a reference framework for SCP, the *supply chain planning matrix* distinguishes SCP activities by *i)* the planning horizon of focus – i.e. long-, mid- and short-term, and the *ii)* supply chain function. These includes sales and demand planning (SAL), procurement planning (PRC), production planning (PRD) and distribution planning (DIS) (Mauergauz, 2016; Stadtler, 2005; Stadtler and Kilger, 2005). A detailed review of the key activities and decisions involved in each process can be found in Stadtler and Kilger (2005).

2.3 Factors affecting BDA adoption decisions in supply chains

A handful of studies have investigated the drivers and barriers (or challenges) for BDA adoption in supply chains, where several of them referred to the Technology-Organization-Environment (TOE) framework for the classification of such factors (Lai et al., 2018; Papadopoulos et al., 2017). To be precise, the TOE framework (Baker, 2012; Tornatzky and Fleischer, 1990) clusters factors determining information system adoption into technological (e.g. perceived benefit, complexity, compliance, availability)

(Arunachalam et al., 2018; Schoenherr and Speier-Pero, 2015), organizational (e.g. organization structure, organizational readiness, organizational culture, availability of resources) (Lamba and Singh, 2018; Sodero et al., 2019) and environmental dimensions (e.g. regulatory environment, security concerns, presence of service providers) (Kache and Seuring, 2017; Queiroz and Telles, 2018; Richey et al., 2016).

3. Methodology

Given the result from literature analysis, this study is developed based on the Delphi method to explore and assess the appropriate match between BDA and SCP, as well as factors affecting BDA adoption decisions in supply chains from a knowledgeable sample of academic and practitioner experts on BDA and SCP.

The Delphi technique is originally developed by the Rand Corporation in the 1950s (Couper, 1984) as a research method that "aims to structure group opinion and discussion" (Goodman, 1987). The key value of the Delphi research method resits in the assurance in obtaining evidence with anonymity between the participants, iteration of results through several rounds, controlled feedback and statistical group response (von der Gracht, 2012). Although several critiques are presented, it remains one of the most prominent research methods when the problem under invetigation benefits from subjective statements, and when more individuals are needed to be effectively involved in discussions to deal with a complex problem (Linstone and Turoff, 1975, 2011). The underpinning RQ of this study deals with the prediction of the current and future use of BDA in SCP, that needs to be built on opinions from scholar and industrial experts with a specific view on the issue. Such aim fits in the value of Delphi studies that converge to predictions on the future through a structured process of consolidating experts' opinion (Kache and Seuring, 2017).

A database was formed with the potential panelists that include scholars, practitioners and solution providers. In particular, the database entails *i)* 103 first authors who had relevant publication in the research field (suggested by Mitchell, 1991), *ii)* 169 practitioners that hold at least five-year experience on planning function within the supply chain, with adequate knowledge on the use of BDA in SCP, and *iii)* 93 practitioners from consultancy firms or software houses that manage the development or adoption of BDA solutions for SCP purpose. The potential panelists include experts from North America (30%) Central Europe (20%), Northern Europe (20%), Asia (14%), Southern Europe (11%) and Pacific (2%). Among this database, it is managed to obtain the professional contact from 236 experts who are invited to participate in the Delphi research online. As there is no strict standard in literature on the number of participants in the Delphi study (Giunipero et al., 2012), and saturation is reached with repetitive patterns in the brainstorming session, our result based on responses from 27 experts (9 academicians, 10 SCP practitioners, and 8 solution providers) can be considered sufficient with an overall response rate of 11%.

This study adopted the Delphi research design with three consecutive rounds, and the data collection was carried out through January to April 2020. One invitation was sent concerning each round, while two reminders were scheduled between the rounds. The entire process of Delphi data collection was carried out in the online form, where the panelists can answer to the survey at their convenience within the given deadline.

The first Delphi round is carried out after a thorough analysis of relevant literature. The experts were asked, in this phase, to nominate and type-in unlimited answers to a series of open-ended questions regarding the prominent BDA model, big data sources and impact of BDA on punctual SCP process (RQ1), as well as factors affecting BDA adoption in supply chains (RQ2). Then intention of this round is to collect all possible nominations from the panel, that could potentially enrich or confirm what is already stated in the literature. To this aim, all the answers were inductively coded by multiple researchers and compared to knowledge from literature, arriving in a list that entails standardized answers from the expert panel. The impact of BDA on SCP for the near future is formulated into projections that summarize the open-ended answers from the panelists. A report was developed as the result of this phase, accompanied by a glossary document containing all useful definitions and examples that serves for disambiguation between the experts and the research team. Both documents were sent to the participants via email while spreading the invitation to the second round.

In the second round, participants were asked to assess the relevance of the entire short-listed responses obtained from the first round, apart from the projections on the impact of BDA on SCP that are assessed for both relevance and probability of occurrence. A report containing all the statistical analysis of the answers from the entire panel was feedback to the participants as input for the next round.

The third round was designed to ask the expert re-evaluating their responses provided in the second round, given the statistical summary on the overall opinion distribution in the panel. Basic indicators on descriptive statistics were provided, including the average, standard deviation and the quartiles. This phase allowed the panelists to communicate and interact with each other in an anonymous manner, avoiding any impact of potential dominant position in the panel. Results from this round were analyzed not only for the basic descriptive statistics, but also the progress on stability (variation of the average) and consensus (convergence rate, interquartile range, coefficient of variation).

4. Findings

4.1 Round 1 result

As explicated in the previous section, experts were asked to answer the open-ended questions in the first round relating to *i)* the prominent BDA model, big data sources and impact of BDA for each punctual SCP process (RQ1), and *ii)* factors affecting BDA adoption in firms and supply chains (RQ2).

The analysis resulted in 10 prominent BDA models respectively for SAL, PRD and DIS, while 9 for PRC. As for big data sources for SCP, the panel highlights respectively 15, 16, 19 and 21 groups of big data sources, and formulated respectively 6, 10, 8 and 11 projections on the impact of BDA on SAL, PRC, PRD and DIS. Data collected on the factors affecting BDA adoption in firms and supply chains resulted in 6, 16, and 7 respectively on the technological, organizational and environmental dimensions according to the TOE model (Baker, 2012; Tornatzky and Fleischer, 1990).

4.2 Round 2 and round 3 result

The second and third round involves quantitative assessment and re-assessment on the items obtained from the previous round. Results from round 2 and 3 prioritized and re-assessed the BDA models that best match each SCP process at the long-, mid-, short term (Table 1), together with a ranking on the most prominent big data sources (Table 2) and projections on the BDA impact (Table 3). Factors that affect BDA adoption were also prioritized respectively for firms and supply chains (Table 4). Analysis of the IQR shows the convergence is reached in more than 70% items.

Due to page limitation, Table 1-4 only presents a fraction (i.e. SAL) of the whole study.

5. Discussion

The result in the previous section can be read with different views. From the perspective of punctual SCP processes, result shed lights on the best match of BDA models, big data sources, and the impact of BDA on the focal process. Take SAL as an example, the study highlights that *simulation* with big data would be the most prominent BDA model for long-term planning ($\bar{x}$=4.59). In combination with the relevant big data sources, it shows that these simulations are likely to be integrated with *data and research on competitors* and *macroeconomic data* ($\bar{x} = 4.40$) to generate prescriptive scenario analysis to inform decisions in the extended time horizon. While big data *forecasting* appears dominant for the mid- ($\bar{x} = 4.4$) and short-term SAL ($\bar{x} = 4.00$), involving analysis with *sales data* and *customer loyalty and behavior*, that supports the fraction of literature that aims to apply unstructured big data (e.g. clickstream data, customer reviews) for mid- and short-term demand forecasting (Boone et al., 2019; Choi, 2018). As such, the significant improvement of forecasting accuracy, and thus, improved customer service level with reducted of stock and costs (SAL1) could be achieved in the long run.

From the managerial perspective, these benefits might be achieved if *resource intensity* is properly managed within firms ($\bar{x}$=4.47) and supply chains ($\bar{x}$=4.65), where adequate training and support are provided to assist the transfer to BDA technology adoption. The presence of *slack resources* is higher weighted at the firm level – as implementation of requires allocation of uncommitted resources (Baker, 2012), while it is more crucial for supply chains to conceptualize the *perceived benefit* ($\bar{x}$=4.47) – as the financial investment (*financial readiness*, $\bar{x}$=4.24) of involving multiple actors should be justified by future return.

Due to page limitation, it is not possible to build extensive discussion in this paper, however evidence offered by this study allows future development in constructing an action roadmap that can tighten up the link between BDA and SCP bridging the technical and managerial perspectives.

6. Conclusion

In short, this paper investigated the link of BDA to the supply chain planning (SCP) processes through the Delphi method. To the best of our knowledge, it is the first study taking SCP as the focus to investigate the integration of BDA to the supply chain domain. The study reveals insight from both academicians and practitioners. In particular, it attempts to match the BDA technology, big data sources and impact to punctual SCP processes, as well as integrating managerial issues affecting the establishment of such by investigating the affecting factors for BDA adoption decisions in supply chains.

Built on the empirical data from scholarly and industrial experts, this study provides managers a reference to explore the potential of BDA in their proprietary supply chains, while being informed on the need of managerial endeavors linked with the adoption of BDA technology.

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Tables

Table 1 Score of BDA model for Sales and Demand planning (SAL)

BDA model	Long-term				Mid-term				Short-term			
	3rd round		2nd round		3rd round		2nd round		3rd round		2nd round	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Simulation	4.59	0.65	3.87	1.25	4.00	0.61	3.96	1.07	3.06	1.22	3.39	1.62
Clustering	4.18	0.77	3.96	1.33	4.06	0.66	3.78	1.04	3.29	1.33	3.30	1.36
Forecasting	4.06	0.95	3.78	1.31	4.29	0.69	4.09	0.95	4.00	SD3	3.83	1.11
Description and Visualization	3.65	0.85	3.57	1.44	3.41	0.94	3.22	1.51	3.24	1.31	3.17	1.56
Association	3.65	1.28	3.57	0.90	3.41	0.94	3.57	0.90	2.76	1.29	3.22	1.28
Feature Selection	3.47	1.07	2.96	1.15	3.24	0.83	3.13	1.10	2.65	0.97	3.04	1.30
Classification	3.47	1.01	3.52	1.16	3.59	0.80	3.65	0.98	3.41	0.94	3.26	1.25
Regression	3.41	1.22	3.52	1.16	3.41	1.12	3.57	1.20	2.82	1.25	3.09	1.41
Optimization	3.24	1.27	3.52	1.47	3.41	1.12	3.30	1.11	3.12	1.25	2.83	1.30
Characterization and Discrimination	3.12	1.11	2.87	1.22	3.12	0.93	3.13	1.01	2.76	1.15	2.83	1.27

Table 2 Score of big data sources for Sales and Demand planning (SAL)

Type	Data origin	BDA Source	Long-term				Mid-tern				Short-term			
			3rd round		2nd round		3rd round		2nd round		3rd round		2nd round	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
n-STR	ENV	Data and research on competitors	4.40	1.00	4.30	0.90	3.90	0.70	4.00	0.90	3.40	1.10	3.60	1.20
n-STR	ENV	Macroeconomic data	4.40	0.70	4.30	0.90	3.50	0.80	3.10	1.10	2.30	0.90	2.30	1.10
STR	ORG	Firm strategy, status, and financial data	4.20	1.30	4.40	0.90	3.60	1.20	3.70	1.10	2.90	1.10	3.20	1.40
STR	ORG	Sales data	3.90	1.00	3.90	0.90	4.20	0.80	4.40	0.60	4.10	1.10	4.40	0.90
n-STR	ORG	Customer loyalty and behavioral data	3.90	0.80	3.80	1.20	4.00	0.60	3.70	1.20	3.60	1.10	3.60	1.30
n-STR	ENV	Policies and regulations data	3.90	1.10	3.70	1.20	3.40	1.00	3.30	0.80	2.70	1.30	2.70	1.20

n-STR	ENV	Data on operating environment	3.80	1.10	3.80	1.30	3.70	1.00	3.90	1.00	3.40	1.40	3.70	1.10
STR	ORG	Forecast data	3.60	1.00	3.70	1.20	4.00	0.90	4.10	0.70	3.90	1.20	4.00	1.10
STR	ORG	Marketing and promotion data	3.60	1.10	3.20	1.30	3.90	0.80	3.80	0.80	4.00	1.30	4.20	1.00
STR	ORG	Data on internal capacity, availability, and constraints	3.50	1.30	3.50	0.90	4.10	1.10	3.90	0.80	4.20	1.10	4.00	0.90
s-STR	ORG	Data from machines and smart objects	3.30	1.00	3.10	1.40	2.80	0.90	2.90	1.30	3.30	1.40	3.10	1.50
STR	ORG	Organizational and production system data	3.10	1.20	3.20	1.30	3.40	0.90	3.80	1.10	3.60	1.30	4.00	1.20
STR	ORG	Accounting data	3.10	1.20	3.00	1.30	3.30	1.00	3.30	1.00	3.20	1.10	3.30	1.10
n-STR	ENV	Social media data	3.00	1.10	3.00	1.30	3.30	1.10	3.40	1.20	3.90	1.40	3.70	1.40
n-STR	ENV	Weather data	2.20	1.20	2.30	1.30	2.70	1.10	2.60	1.30	3.60	1.20	3.20	1.40

Table 3 Scores of the relevance and probability of occurrence for BDA projections on supply chains

		Relevance				**Probability of occurrence**			
Projections		**3rd round**		**2nd round**		**3rd round**		**2nd round**	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
SAL1.	BDA will bring significant improvement in forecasting accuracy in sales and demand planning, and therefore, leads to better customer service level, reduction of stock and costs, and avoidance of stockout.	4.50	0.50	4.30	0.70	3.80	1.10	3.70	1.10
SAL2.	BDA will largely enhance flexibility and automation in sales and demand planning	3.90	0.90	3.80	0.90	3.80	0.80	3.50	1.00
SAL3.	BDA will revolutionize mid-term sales planning for the visibility it brings on customers and mark	4.20	0.70	4.40	0.50	3.40	1.00	3.40	1.00
SAL4.	BDA will significantly support product programs definition by empowering market analysis to detect new business opportunities	3.90	0.70	4.10	0.90	3.10	1.10	3.50	1.00
SAL5.	BDA will empower short-term sales planning and demand planning for individuals with customer-generated big data	3.90	1.00	4.00	1.10	3.80	0.80	3.70	1.30
SAL6.	BDA will facilitate automatic forecast adaption (update) according to customer behaviour in real-time	3.90	0.90	3.90	1.10	3.40	1.00	3.40	1.50
PRC1.	BDA will bring significant performance improvement in Procurement planning (e.g. higher planning accuracy, cost reduction, better material program, order management.	3.90	1.00	3.90	1.10	3.20	0.90	3.40	0.90

PRC2.	BDA will largely improve the performance of supplies (e.g. raw material quality, service level) as outcome of the Procurement planning process	3.80	1.00	3.70	1.00	3.10	1.00	3.00	1.00
PRC3.	BDA will empower fast response to procurement disruptions by prior risk detection	4.10	1.00	3.90	1.10	3.40	0.90	3.20	1.20
PRC4	BDA will enhance sustainability (e.g. greenhouse gas reduction, waste management) in Procurement planning	3.90	1.10	4.20	0.80	3.40	1.20	3.30	1.00
PRC5.	BDA will empower supplier selection and supply base definition by using more granular supplier performance data (e.g. price, quality, delivery performance) in long-term Procurement planning	3.80	1.00	4.00	1.00	3.40	1.10	3.30	1.20
PRC6.	BDA will empower the detection of procurement-related trends in long-term Procurement planning	3.90	1.10	4.00	0.90	3.20	1.00	3.30	1.00
PRC7.	BDA will facilitate collaboration with suppliers in long-term Procurement planning	4.00	1.10	3.90	1.00	2.90	1.20	3.30	1.10
PRC8.	BDA will significantly support optimization in inbound inventories of raw materials and components (e.g. stock reduction, stockout reduction)	3.80	1.10	3.90	0.90	3.60	1.20	3.60	0.90
PRC9.	BDA will provide fundamental support to supplier negotiations and improve contract terms by scenario analysis with more accurate big data	3.90	1.10	3.70	1.20	3.40	1.10	3.00	1.10
PRC10.	BDA will improve process standardization and automation in materials ordering in short-term Procurement planning	3.60	1.10	3.30	1.00	3.30	1.10	3.10	1.40
PRD1.	BDA will bring significant performance improvement in Production planning (e.g. higher planning accuracy, better customers service level, cost reduction)	3.80	1.10	4.20	0.80	3.50	1.00	3.70	0.90
PRD2.	BDA will empower fast response to production disruptions through prior risk detection	3.90	1.20	4.00	0.90	3.40	1.00	3.40	1.10
PRD3.	BDA will enhance sustainability (e.g. emission and waste reduction) in Production planning	3.60	1.10	3.70	1.20	2.80	1.00	2.90	1.00
PRD4.	BDA will empower supply network design (e.g. production plant location, warehouse location) with the use of better and new data sources	3.60	1.10	3.80	1.10	3.20	1.00	3.10	1.20
PRD5.	BDA will empower production system design (e.g. production capacity sizing, plan layout, asset and equipment investment) by scenario analysis and simulations	3.80	1.10	3.70	1.20	3.20	1.30	3.00	1.30
PRD6.	BDA will empower the detection of production-related trends and growth opportunities in long-term Production planning	3.80	1.10	3.80	1.10	3.10	1.10	3.00	1.10
PRD7.	BDA will significantly support optimization of production inventories (e.g. stock reduction, stockout reduction)	4.10	1.10	4.00	1.10	3.60	1.20	3.90	1.10
PRD8.	BDA will provide fundamental support to optimizations in master production scheduling and capacity planning	4.20	1.00	4.20	0.70	3.50	1.20	4.00	1.00

PRD9.	BDA will revolutionize machine scheduling and optimization of lot-sizing at shopfloor level with timely capacity adjustments and re-scheduling based on machine-state and operational data	3.90	1.00	4.10	1.10	3.80	1.20	4.00	1.20
DIS1.	BDA will bring significant performance improvement in Distribution planning (e.g. better customer service level, cost reduction, higher planning accuracy)	4.10	1.00	4.00	1.00	3.40	0.90	3.40	1.00
DIS2.	BDA will empower fast response to distribution disruptions through prior risk detection	4.10	1.00	4.00	1.00	3.40	1.20	3.50	1.20
DIS3.	BDA will enhance sustainability in Distribution planning (e.g. reduction of carbon footprint)	3.90	1.00	3.80	1.20	2.90	1.00	3.10	1.20
DIS4.	BDA will empower distribution make-or-buy choice and investment justification in long-term Distribution planning	3.90	0.90	3.70	1.10	3.00	1.00	2.90	1.20
DIS5.	BDA will provide fundamental support to distribution network design (e.g. location of distribution centers, warehouses and deposits)	4.10	1.00	4.10	0.90	3.60	1.10	3.40	1.20
DIS6.	BDA will support optimization of mid-term (weekly to monthly) distribution planning (e.g. workflow aggregation, better distribution mode selection)	3.60	1.10	4.00	0.80	3.20	1.20	3.40	1.20
DIS7.	BDA will empower the detection of distribution-related trends in long-term Distribution planning	3.60	1.10	3.70	1.00	3.10	1.10	3.30	1.20
DIS8.	BDA will significantly support optimization of inventories in distribution system and warehouse layout	4.00	1.00	4.00	0.80	3.50	1.10	3.70	1.20
DIS9.	BDA will empower mid-term distribution planning and personnel scheduling (e.g. workflow aggregation, better distribution mode selection) in distribution systems with the use of better and new data sources	3.70	1.10	3.80	0.70	3.10	1.40	3.40	1.10
DIS10.	BDA will provide fundamental support to short-term transportation planning with use of real-time data to reduce waste and time	3.90	1.00	4.10	1.00	3.50	1.20	3.70	1.40
DIS11.	BDA will largely improve planning on warehouse replenishments with real-time and granular consumption data	4.30	1.00	4.40	0.70	3.60	1.40	4.10	1.10

Table 4 Score on factors affecting BDA adoption in firms and supply chains

Cluster	Factor	Firm				Supply chain			
		3rd round		2nd round		3rd round		2nd round	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Org	Resource intensity	4.47	1.12	3.26	1.18	4.65	0.49	3.04	1.22
Org	Presence of slack resources	4.35	0.70	3.04	1.19	3.82	1.01	3.30	1.06
Org	Financial readiness	4.12	0.86	3.74	1.21	4.24	0.66	3.35	1.19
Org	Organizational culture	4.12	1.05	3.78	0.95	4.12	1.05	3.83	1.03
Org	Top management support	4.12	0.70	4.30	1.11	3.88	1.11	4.35	0.98
Org	Interconnectedness	3.88	0.93	3.43	0.99	3.82	0.95	3.52	1.16
Org	Organizational stability	3.88	1.05	3.87	1.01	3.65	1.32	3.61	0.72
Org	Global scope	3.82	0.88	3.61	1.12	3.82	1.38	3.65	1.19
Env	Security and privacy concerns	3.82	1.13	3.74	1.10	3.65	1.17	3.43	1.16
Org	Experience in change management program	3.76	0.90	3.74	1.25	3.76	1.03	3.87	1.01
Org	Organizational size	3.76	1.20	3.22	0.90	3.53	0.94	3.22	1.09
Tec	Perceived benefit	3.76	1.09	3.91	1.16	4.47	0.87	4.04	0.93
Env	Technology adoption of competitors	3.76	0.75	3.48	1.20	4.00	0.79	3.48	1.31
Org	Organization strategy	3.71	0.77	4.04	0.64	4.12	0.78	3.87	0.97
Org	Technological adoption capability	3.71	0.92	3.83	0.83	3.94	0.83	4.13	0.76
Tec	Relative advantage	3.59	1.06	3.52	1.08	4.35	0.93	3.61	1.03
Tec	Availability of the technology	3.53	0.94	3.52	1.24	3.18	1.19	3.70	1.40
Env	Business partners pressure	3.53	0.94	3.48	1.24	3.71	1.10	3.70	1.11
Org	Sc connectivity and integration	3.47	1.18	3.48	1.04	4.06	1.20	4.26	0.96
Env	Presence of technology service providers	3.47	1.01	3.30	1.22	3.47	1.12	3.39	1.31
Org	IT infrastructure and expertise	3.41	1.06	4.09	0.79	3.53	1.18	4.04	1.02
Org	Sc stability	3.41	1.06	3.43	1.20	4.00	1.12	3.96	1.02
Env	Technology trend	3.41	1.06	3.30	1.33	3.65	1.22	3.48	1.31
Tec	Complexity (of the technology)	3.29	0.92	3.48	1.12	3.29	1.16	3.61	1.16
Org	Supply chain strategy	3.24	1.03	3.70	1.06	-	-	-	-
Env	Industry structure	3.18	1.01	3.17	0.89	3.53	1.01	3.65	0.98
Tec	Data quality	3.12	1.11	3.83	1.15	3.76	1.15	3.96	1.15
Tec	Compatibility and scalability	2.82	1.07	3.52	1.04	3.00	1.22	3.78	1.17
Env	Regulatory environment	2.82	1.01	3.26	1.21	3.06	1.14	3.09	1.24